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Accelerated oblique random survival forests

Byron C. Jaeger bjaeger@wakehealth.edu
Department of Biostatistics and Data Science
Wake Forest University School of Medicine
Winston-Salem, NC 27157, USA

Sawyer Welden swelden@wakehealth.edu
Department of Biostatistics and Data Science
Wake Forest University School of Medicine
Winston-Salem, NC 27157, USA

Kristin Lenoir klenoir@wakehealth.edu
Department of Biostatistics and Data Science
Wake Forest University School of Medicine
Winston-Salem, NC 27157, USA

Jaime L Speiser jspeiser@wakehealth.edu
Department of Biostatistics and Data Science
Wake Forest University School of Medicine
Winston-Salem, NC 27157, USA

Matthew Segar Matthew.Segar@UTSouthwestern.edu
Division of Cardiology, Department of Internal Medicine,
University of Texas Southwestern Medical Center, Dallas

Nicholas M. Pajewski npajewsk@wakehealth.edu
Department of Biostatistics and Data Science
Wake Forest University School of Medicine
Winston-Salem, NC 27157, USA

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Abstract

The oblique random survival forest (ORSF) is an ensemble method for supervised learning that extends the random survival forest (RSF). Trees in the ORSF are grown using linear combinations of variables to create branches in the tree, whereas in the RSF a single variable is used. ORSF ensembles often have higher prediction accuracy than RSF ensembles, but the additional computational overhead of fitting ORSF ensembles limits their scope of application. In addition, few methods have been developed for interpretation of ORSF ensembles. In this article, we introduce and evaluate methods to accelerate the ORSF (that is, reduce computational overhead) and compute the importance of individual variables in the ORSF We show that our strategy to accelerate the ORSF is up to 500 times faster than existing software for ORSFs (the `obliqueRSF` R package), and that prediction accuracy of the accelerated ORSF is equivalent or superior to that of existing ORSF methods. We estimate importance of variables for the ORSF by negating each coefficient used for the given variable in linear combinations, and then computing the reduction in out-of-bag accuracy. We show with simulation that 'negation importance' can discriminate between signal and noise variables, and it outperforms several state-of-the-art variable importance techniques in this task when there is correlation among predictors.

Keywords: Random Forests, Survival, Efficient, Variable Importance

1. Introduction

Risk prediction can reduce the burden of disease by educating patients and providers and guiding strategies to prevent and treat disease in a wide range of medical domains (Moons et al., 2012a,b). The random survival forest (RSF), a supervised learning algorithm that can engage with censored outcomes, is frequently used for risk prediction. Notable characteristics of the RSF include uniform convergence of its ensemble survival function to the true population survival function when the predictor space is discrete (Ishwaran and Kogalur, 2010). In addition, software implementing the RSF is freely available, extremely efficient, and full of tools to interpret and explain the RSF (Ishwaran and Kogalur, 2019; Wright and Ziegler, 2017; Hothorn et al., 2010). However, there remains considerable potential to improve the RSF in risk prediction tasks where training samples are not large enough to guarantee asymptotic properties or predictor spaces are non-discrete (that is, predictors are continuous).

RSFs may be axis based or oblique. The axis based RSF uses a single predictor whereas the oblique RSF uses a linear combination of predictors to create branches in trees. While axis based decision boundaries are always perpendicular to the axis of the relevant predictor, linear combinations of predictors create oblique decision boundaries that are neither parallel nor perpendicular to axes of their contributing predictors. Prior work has found the oblique RSF has higher prediction accuracy than the axis based RSF in general benchmarks (Jaeger et al., 2019) and that oblique splitting is particularly effective when predictors are continuous (Menze et al., 2011). However, existing methods to implement oblique splitting typically use fully trained models in each non-leaf node to identify linear combinations of predictors, exponentially increasing the number of operations required for the oblique RSF versus its axis based counterpart. In addition, standard methods to estimate variable importance (VI) in the RSF are less effective in the oblique RSF, and few methods have been introduced to estimate VI specifically for the oblique RSF.

The aim of this article is to improve the computational efficiency and interpretability of the oblique RSF. In a general benchmark experiment including YYYY risk prediction tasks, we show that oblique RSFs with partially trained models have equivalent or superior prediction accuracy and are orders of magnitude more efficient than oblique RSFs with fully trained models in non-leaf nodes. We introduce a method to estimate VI for oblique RSFs and compare its ability to discriminate between signal and noise variables versus standard and state-of-the-art methods. All methods proposed in this article are available in the `aorsf` R Package.

2. Related work

2.1 Axis-based and oblique random forests

After Breiman (2001) introduced the axis-based and oblique random forest (RF), numerous methods were developed to grow oblique RFs for classification or regression tasks (Menze et al., 2011; Zhang and Suganthan, 2014; Rainforth and Wood, 2015; Zhu et al., 2015; Poona et al., 2016; Qiu et al., 2017; Tomita et al., 2020; Katuwal et al., 2020). However, oblique splitting approaches for classification or regression may not generalize to survival tasks (for example, see Zhu, 2013, Section 4.5.1), and most research involving the RSF has focused on forests with axis-based trees (Wang and Li, 2017).

Building on prior research for bagging survival trees (Hothorn et al., 2004), Hothorn et al. (2006) developed an axis-based RSF in their framework for unbiased recursive partitioning, more commonly referred to as the conditional inference forest (CIF). Zhou et al. (2016) developed a rotation forest based on the CIF and Wang and Zhou (2017) developed a method for extending the predictor space of the CIF. Ishwaran et al. (2008) developed an axis-based RSF with strict adherence to the rules for growing trees proposed in Breiman (2001). Jaeger et al. (2019) developed the oblique RSF following the bootstrapping approach described in Breiman's original RF and incorporating early stopping rules from the CIF.

2.2 Variable importance

Breiman (2001) introduced permutation VI, defined for each predictor as the difference in a RF's estimated generalization error before versus after the predictor's values are randomly permuted. Strobl et al. (2007) identified bias in permutation VI driven by variable selection bias and effects induced by bootstrap sampling, and proposed an unbiased permutation VI based on unbiased recursive partitioning (see Hothorn et al. (2006)). Menze et al. (2011) introduced an approach to estimate VI for oblique RFs that computes an analysis of variance (ANOVA) table in non-leaf nodes to obtain p-values for each predictor contributing to the node. The ANOVA VI[1] is then defined for each predictor as the number of times a p-value associated with the predictor is ≤ 0.01 while growing a forest. Lundberg and Lee (2017) introduced a method to estimate VI using SHapley Additive exPlanation (SHAP) values, which estimate the contribution of a predictor to a model's prediction for a given observation. SHAP VI is computed for each predictor by taking the mean absolute value of SHAP values for that predictor across all observations in a given set.

3. Novel techniques for oblique random survival forests

Consider the usual framework for survival analysis with training data

$$\mathcal{D}_{\text{train}} = \{(T_i, \delta_i, \boldsymbol{x}_i)\}_{i=1}^{N_{\text{train}}}.$$

Here, T_i is the event time if $\delta_i = 1$ and last point of contact if $\delta_i = 0$, and $\boldsymbol{x}_i$ is a vector of predictors values. Assuming there are no ties, let $t_1 < \ldots < t_m$ denote the m unique event times in $\mathcal{D}_{\text{train}}$.

3.1 Partial training at non-leaf nodes

We propose to identify linear combinations of predictor variables in non-leaf nodes by applying Newton Raphson scoring to the partial likelihood function of the Cox regression model:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{m} \frac{e^{\boldsymbol{x}_{j(i)}^T \boldsymbol{\beta}}}{\sum_{j \in R_i} e^{\boldsymbol{x}_j^T \boldsymbol{\beta}}}, \tag{1}$$

where R_i is the set of indices, j, with $T_j \geq t_i$ (i.e., those still at risk at time t_i), and $j(i)$ is the index of the observation for which an event occurred at time t_i. The `survival` package includes documentation that outlines how to complete this estimation procedure efficiently (see Therneau, 2022, exact.nw). Briefly, a vector of estimated regression coefficients, $\hat{\beta}$, is updated in each step of the procedure based on its first derivative, $U(\hat{\beta})$, and second derivative, $H(\hat{\beta})$:

$$\hat{\beta}^{k+1} = \hat{\beta}^k + U(\hat{\beta} = \hat{\beta}^k)\, H^{-1}(\hat{\beta} = \hat{\beta}^k)$$

It is vital to cycle through iterations until a convergence threshold is met for statistical inference, but it is only necessary to complete one iteration to identify coefficients for a linear combination of predictors. Jaeger et al. (2019) identified linear combinations using penalized regression models, which supply more flexible solutions for $\hat{\beta}$ at the cost of greater computational demand.

1. Menze et al. (2011) name their method 'oblique RF VI', but we use the name 'ANOVA VI' in this article to avoid confusing Menze's approach with other approaches to estimate VI for oblique RFs.

3.2 Negation variable importance

Negation VI is similar to permutation VI in that it measures how much a model's prediction error increases when a variable's role in the model is de-stabilized. More specifically, negation VI measures the increase in an oblique RF's prediction error after flipping the sign of all coefficients linked to a variable (that is, negating them). As the magnitude of a coefficient increases, so does the probability that negating it will change the oblique RF's predictions. Since the coefficients in each non-leaf node of an oblique RFs are adjusted for the accompanying predictors, negation VI may provide better estimation of VI in the presence of correlated variables compared to standard VI techniques. Although the current article focuses on oblique RSFs, negation VI can be applied to any oblique RF.

4. Numeric experiments

4.1 Benchmark of prediction accuracy

4.1.1 Learners

We consider four classes of learners: RFs, boosting ensembles, regression models, and neural networks (Table 1). For RF learners, the number of observations required in terminal nodes was fixed at 10, the number of randomly selected predictors was the square root of the total number of predictors rounded to the nearest integer, and the number of trees in the ensemble was 500. For boosting, regression, and neural network learners, nested cross-validation was applied to tune each model, that is, assess multiple possible values for relevant model parameters and use the values that optimize the model's estimated prediction accuracy. Specifically, tuning for boosting models included identifying the number of steps to complete. For regression models, tuning was used to identify the magnitude of penalization. For neural networks, the number and density of layers was tuned.

Learner Class	Software	Learners	Description
Random Survival Forests			

Axis based	`RandomForestSRC`
	`ranger`
	`party`
	`rotsf`
	`rsfse`
		`rsf-standard`
		`rsf-extratrees`
		`cif-standard`
		`cif-rotate`
		`cif-spacextend`
			`rsf-standard` grows survival trees following Leo Breiman's original random forest algorithm with variables and cut-points selected to maximize a log-rank statistic. `rsf-extratrees` grows survival trees with randomly selected features and cut-points. `cif-standard` uses the framework of conditional inference to grow survival trees. `cif-rotate` extends `cif-standard` by applying principal component analysis to random subsets of data prior to growing each survival tree. `cif-spacextend` derives new predictors for each tree in the ensemble, separately.

Oblique	`obliqueRSF`
	`aorsf`
		`obliqueRSF-net`
		`aorsf-net`
		`aorsf-fast`
		`aorsf-cph`
		`aorsf-extratrees`
			Oblique survival trees following Leo Breiman's random forest algorithm. Linear combinations of inputs are derived using `glmnet` in `obliqueRSF-net` and `aorsf-net`, using Newton Raphson scoring for the Cox partial likelihood function in `aorsf-fast` and `aorsf-cph`, and chosen randomly from a uniform distribution in `aorsf-extratrees`. Cut-points are selected to maximize a log-rank statistic.

Boosting ensembles			
Trees	`xgboost`	`xgboost-cox` `xgboost-aft`	`xgboost-cox` maximizes the Cox partial likelihood function, whereas `xgboost-aft` maximizes the accelerated failure time likelihood function. Nested cross validation (5 folds) is applied to tune the number of trees grown, the minimum number of observations in a leaf node was 10, the maximum depth of trees was 6, and $\sqrt{p}$ variables were considered randomly for each tree split, where p is the total number of predictors.
Regression models			
Cox Net	`glmnet`	`glmnet-cox`	The Cox proportional hazards model is fit using an elastic net penalty. Nested cross validation (5 folds) is applied to tune penalty terms.
Neural networks			
Cox Time	`survivalmodels`	`nn-cox`	A neural network based on the proportional hazards model with time-varying effects. Nested cross-validation was applied to select the number of layers (from 1 to 8), the number of nodes in each layer (from $\sqrt{p}/2$ to $\sqrt{p}$), and the number of epochs to complete (up to 500). A drop-out rate of 10% was applied during training.

Table 1: Learning algorithms assessed in numeric studies

4.1.2 Evaluation of prediction accuracy

Our primary metric for evaluating the accuracy of predicted risk is the integrated and scaled Brier score (Graf et al., 1999). Consider a testing data set:

$$\mathcal{D}_{\text{test}} = \{(T_i, \delta_i, x_i)\}_{i=1}^{N_{\text{test}}}.$$

Let $\widehat{S}(t \mid x_i)$ be the predicted probability of survival up to a given prediction horizon of $t > 0$. For observation i in $\mathcal{D}_{\text{test}}$, let $\widehat{S}(t \mid \boldsymbol{x}_i)$ be the predicted probability of survival up to a given prediction horizon of $t > 0$. Define

$$\begin{aligned}\widehat{\mathrm{BS}}(t) = \frac{1}{N_{\text{test}}} \sum_{i=1}^{N_{\text{test}}} \{&\widehat{S}(t \mid \boldsymbol{x}_i)^2 \cdot I(T_i \leq t, \delta_i = 1) \cdot \widehat{G}(T_i)^{-1} \\ &+ [1 - \widehat{S}(t \mid \boldsymbol{x}_i)]^2 \cdot I(T_i > t) \cdot \widehat{G}(t)^{-1}\}\end{aligned}$$

where $\widehat{G}(t)$ is the Kaplan-Meier estimate of the censoring distribution. As $\widehat{\mathrm{BS}}(t)$ is time dependent, integration over time provides a summary measure of performance over a range of plausible prediction horizons. The integrated $\widehat{\mathrm{BS}}(t)$ is defined as

$$\widehat{\mathcal{BS}}(t_1, t_2) = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} \widehat{\mathrm{BS}}(t)dt. \tag{2}$$

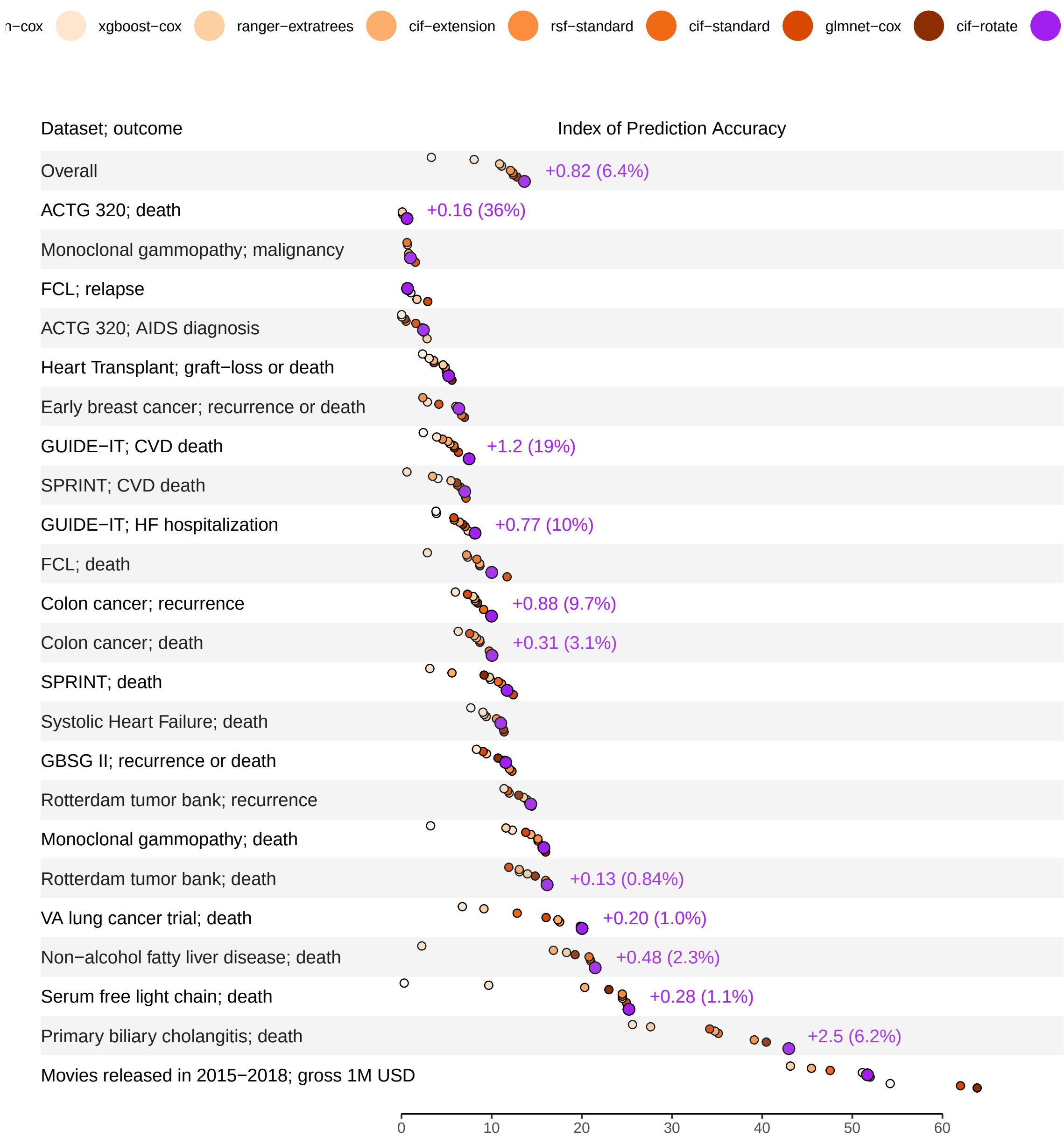
In our results, t_1 and t_2 are the 25th and 75th percentile of event times, respectively. $\widehat{\mathcal{BS}}(t_1, t_2)$, a sum of squared prediction errors, can be scaled to produce a measure of explained residual variation (that is, an R^2 statistic) by computing

$$R^2 = 1 - \frac{\widehat{\mathcal{BS}}(t_1, t_2)}{\widehat{\mathcal{BS}}_0(t_1, t_2)} \tag{3}$$

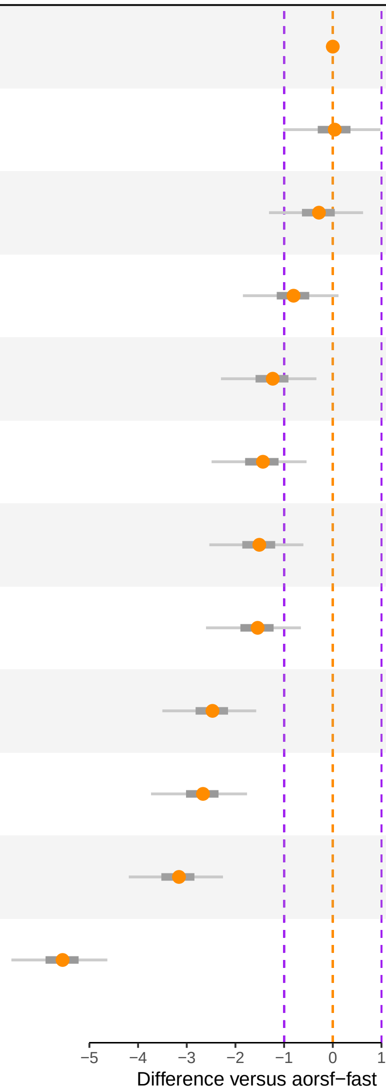
where $\widehat{\mathcal{BS}}_0(t_1, t_2)$ is the integrated Brier score when a Kaplan-Meier estimate for survival based on the training data is used as the survival prediction function $\widehat{S}(t)$. We refer to this R^2 statistic as the index of prediction accuracy and we scale its values by 100 to avoid unnecessary leading zero's. For example, we present 25 if R^2 is 0.25 and present 10.2 if the difference between two R^2 is 0.102.

4.1.3 Statistical analysis

4.1.4 Results


n−cox
xgboost−cox
ranger−extratrees
cif−extension
rsf−standard
cif−standard
glmnet−cox
cif−rotate
Dataset; outcome
Index of Prediction Accuracy
Overall
+0.82 (6.4%)
ACTG 320; death
+0.16 (36%)
Monoclonal gammopathy; malignancy
FCL; relapse
ACTG 320; AIDS diagnosis
Heart Transplant; graft−loss or death
Early breast cancer; recurrence or death
GUIDE−IT; CVD death
+1.2 (19%)
SPRINT; CVD death
GUIDE−IT; HF hospitalization
+0.77 (10%)
FCL; death
Colon cancer; recurrence
+0.88 (9.7%)
Colon cancer; death
+0.31 (3.1%)
SPRINT; death
Systolic Heart Failure; death
GBSG II; recurrence or death
Rotterdam tumor bank; recurrence
Monoclonal gammopathy; death
Rotterdam tumor bank; death
+0.13 (0.84%)
VA lung cancer trial; death
+0.20 (1.0%)
Non−alcohol fatty liver disease; death
+0.48 (2.3%)
Serum free light chain; death
+0.28 (1.1%)
Primary biliary cholangitis; death
+2.5 (6.2%)
Movies released in 2015−2018; gross 1M USD
0
10
20
30
40
50
60

Learner	Scaled integrated Brier score	Posterior probability: Equivalence	Posterior probability: Difference < 0	Posterior probability: Difference < −1
aorsf−fast		---	---	---
aorsf−cph		0.95	0.46	0.03
aorsf−net		0.91	0.72	0.09
cif−rotate		0.65	0.96	0.35
cif−standard		0.31	1.00	0.69
glmnet−cox		0.17	1.00	0.83
rsf−standard		0.15	1.00	0.85
obliqueRSF−net		0.13	1.00	0.87
cif−extension		0.00	1.00	1.00
ranger−extratrees		0.00	1.00	1.00
aorsf−random		0.00	1.00	1.00
xgboost−cox		0.00	1.00	1.00



4.2 Benchmark of variable selection

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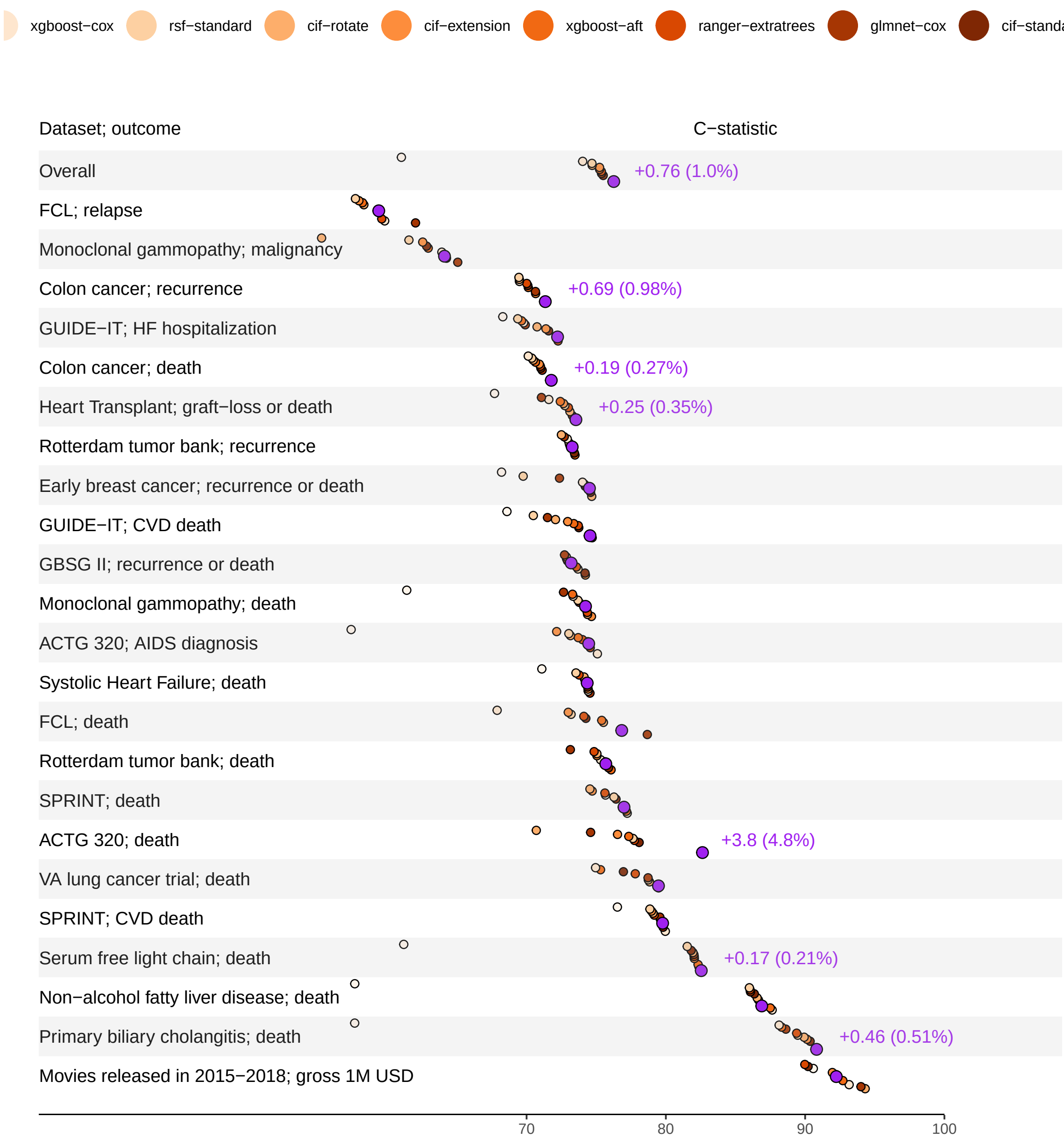
Appendix A.


xgboost−cox
rsf−standard
cif−rotate
cif−extension
xgboost−aft
ranger−extratrees
glmnet−cox
cif−standar
Dataset; outcome
C−statistic
Overall
+0.76 (1.0%)
FCL; relapse
Monoclonal gammopathy; malignancy
Colon cancer; recurrence
+0.69 (0.98%)
GUIDE−IT; HF hospitalization
Colon cancer; death
+0.19 (0.27%)
Heart Transplant; graft−loss or death
+0.25 (0.35%)
Rotterdam tumor bank; recurrence
Early breast cancer; recurrence or death
GUIDE−IT; CVD death
GBSG II; recurrence or death
Monoclonal gammopathy; death
ACTG 320; AIDS diagnosis
Systolic Heart Failure; death
FCL; death
Rotterdam tumor bank; death
SPRINT; death
ACTG 320; death
+3.8 (4.8%)
VA lung cancer trial; death
SPRINT; CVD death
Serum free light chain; death
+0.17 (0.21%)
Non−alcohol fatty liver disease; death
Primary biliary cholangitis; death
+0.46 (0.51%)
Movies released in 2015−2018; gross 1M USD
70
80
90
100

	Performance metric (SD)		Computing time, seconds			
			Fit model		Predict risk	
	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
Overall						
aorsf-cph	0.133 (0.124)	0.757 (0.079)	0.830	2.74	0.070	0.980
aorsf-fast	0.133 (0.124)	0.757 (0.080)	0.302	1.00	0.072	1.00
aorsf-net	0.130 (0.127)	0.755 (0.080)	61.237	202.6	0.069	0.964
cif-rotate	0.125 (0.145)	0.741 (0.092)	30.623	101.3	7.208	100.3
cif-standard	0.120 (0.111)	0.748 (0.079)	2.035	6.73	5.128	71.3
glmnet-cox	0.119 (0.139)	0.748 (0.083)	0.253	0.837	0.005	0.070
rsf-standard	0.118 (0.128)	0.741 (0.084)	1.694	5.60	0.152	2.11
obliqueRSF-net	0.117 (0.094)	0.754 (0.080)	328.883	1,087.9	26.636	370.5
cif-extension	0.108 (0.108)	0.746 (0.083)	13.510	44.7	6.840	95.2
ranger-extratrees	0.106 (0.097)	0.748 (0.076)	0.692	2.29	0.264	3.68
aorsf-random	0.101 (0.092)	0.735 (0.074)	1.879	6.22	0.066	0.919
xgboost-cox	0.077 (0.114)	0.736 (0.095)	3.833	12.7	0.005	0.070
nn-cox	0.030 (0.118)	0.610 (0.128)	15.427	51.0	1.513	21.0
xgboost-aft	-3.68 (4.86)	0.747 (0.082)	13.182	43.6	0.008	0.117
ACTG 320; AIDS diagnosis, n = 1151, p = 12						
aorsf-random	0.028 (0.022)	0.748 (0.038)	0.637	4.19	0.040	1.06
ranger-extratrees	0.028 (0.017)	0.740 (0.036)	0.061	0.404	0.184	4.81
obliqueRSF-net	0.027 (0.022)	0.746 (0.038)	27.286	179.6	15.729	411.6
aorsf-cph	0.025 (0.029)	0.751 (0.042)	0.450	2.97	0.034	0.891
cif-standard	0.024 (0.031)	0.744 (0.040)	1.608	10.6	4.825	126.3
aorsf-fast	0.024 (0.028)	0.745 (0.044)	0.152	1.00	0.038	1.00
cif-extension	0.023 (0.015)	0.722 (0.038)	9.788	64.4	4.595	120.2
aorsf-net	0.019 (0.034)	0.745 (0.042)	20.231	133.2	0.038	0.995
glmnet-cox	0.016 (0.030)	0.746 (0.037)	0.183	1.21	0.002	0.053
rsf-standard	0.005 (0.041)	0.730 (0.042)	0.235	1.55	0.071	1.85
cif-rotate	0.004 (0.040)	0.731 (0.038)	15.089	99.3	4.246	111.1
xgboost-cox	0.000 (0.044)	0.751 (0.033)	3.655	24.1	0.003	0.079
nn-cox	0.000 (0.013)	0.574 (0.117)	12.345	81.3	0.639	16.7
xgboost-aft	-8.40 (1.81)	0.737 (0.035)	11.029	72.6	0.007	0.183
ACTG 320; death, n = 1151, p = 12						
obliqueRSF-net	0.007 (0.012)	0.819 (0.051)	9.302	102.7	10.943	545.1
aorsf-cph	0.007 (0.019)	0.815 (0.058)	0.363	4.00	0.020	1.00
aorsf-fast	0.006 (0.019)	0.820 (0.054)	0.091	1.00	0.020	1.00
aorsf-random	0.004 (0.015)	0.780 (0.070)	0.326	3.60	0.026	1.30

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
ranger-extratrees	0.001 (0.020)	0.773 (0.071)	0.045	0.497	0.143	7.13
cif-extension	0.001 (0.021)	0.759 (0.061)	8.354	92.2	3.905	194.5
xgboost-cox	-0.004 (0.004)	0.500 (0.000)	0.120	1.32	0.002	0.100
nn-cox	-0.004 (0.004)	0.535 (0.110)	11.322	125.0	0.689	34.3
cif-standard	-0.006 (0.026)	0.773 (0.056)	1.758	19.4	4.361	217.2
aorsf-net	-0.006 (0.033)	0.799 (0.065)	15.227	168.1	0.025	1.25
rsf-standard	-0.031 (0.053)	0.769 (0.069)	0.090	0.994	0.038	1.90
cif-rotate	-0.037 (0.052)	0.704 (0.094)	13.476	148.8	3.663	182.5
glmnet-cox	-0.062 (0.092)	0.736 (0.098)	0.301	3.33	0.001	0.051
xgboost-aft	-24.3 (7.36)	0.767 (0.066)	10.846	119.7	0.008	0.399
Colon cancer; death, n = 929, p = 12						
aorsf-fast	0.100 (0.014)	0.718 (0.011)	0.289	1.00	0.075	1.00
aorsf-cph	0.100 (0.014)	0.717 (0.011)	0.691	2.39	0.070	0.945
cif-standard	0.097 (0.013)	0.710 (0.012)	1.529	5.29	5.019	67.4
aorsf-net	0.097 (0.014)	0.717 (0.012)	55.870	193.4	0.064	0.853
aorsf-random	0.096 (0.010)	0.716 (0.011)	1.612	5.58	0.066	0.879
obliqueRSF-net	0.089 (0.006)	0.717 (0.012)	269.561	932.9	44.243	593.8
cif-rotate	0.087 (0.017)	0.705 (0.014)	15.603	54.0	6.291	84.4
rsf-standard	0.087 (0.019)	0.704 (0.011)	1.646	5.70	0.143	1.92
ranger-extratrees	0.083 (0.007)	0.710 (0.011)	0.735	2.54	0.263	3.53
cif-extension	0.081 (0.006)	0.709 (0.011)	8.523	29.5	5.850	78.5
glmnet-cox	0.076 (0.016)	0.711 (0.019)	0.132	0.457	0.004	0.054
xgboost-cox	0.063 (0.013)	0.701 (0.013)	3.266	11.3	0.004	0.054
nn-cox	-0.013 (0.040)	0.506 (0.042)	14.970	51.8	1.780	23.9
xgboost-aft	-1.11 (0.200)	0.706 (0.013)	12.660	43.8	0.007	0.094
Colon cancer; recurrence, n = 929, p = 12						
aorsf-fast	0.100 (0.017)	0.713 (0.016)	0.282	1.00	0.069	1.00
aorsf-cph	0.099 (0.017)	0.712 (0.016)	0.708	2.52	0.070	1.01
aorsf-net	0.096 (0.018)	0.713 (0.017)	51.056	181.3	0.065	0.937
cif-standard	0.091 (0.015)	0.701 (0.017)	1.183	4.20	4.109	59.2
obliqueRSF-net	0.088 (0.008)	0.711 (0.015)	298.417	1,059.9	44.698	643.9
aorsf-random	0.087 (0.012)	0.703 (0.015)	1.629	5.78	0.064	0.923
cif-rotate	0.084 (0.020)	0.695 (0.017)	14.130	50.2	6.064	87.4
cif-extension	0.082 (0.009)	0.707 (0.017)	8.587	30.5	6.571	94.7
rsf-standard	0.081 (0.020)	0.694 (0.015)	1.408	5.00	0.139	2.00
ranger-extratrees	0.079 (0.011)	0.700 (0.016)	0.555	1.97	0.235	3.39
glmnet-cox	0.073 (0.018)	0.706 (0.024)	0.161	0.572	0.005	0.072

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
xgboost-cox	0.060 (0.011)	0.695 (0.018)	3.088	11.0	0.004	0.058
nn-cox	-0.005 (0.005)	0.506 (0.039)	13.814	49.1	1.499	21.6
xgboost-aft	-1.20 (0.239)	0.701 (0.019)	11.979	42.5	0.007	0.101
Early breast cancer; recurrence or death, n = 614, p = 1692						
obliqueRSF-net	0.073 (0.024)	0.749 (0.027)	1951.148	2,519.7	15.143	83.8
cif-rotate	0.072 (0.017)	0.748 (0.027)	6765.191	8,736.4	351.642	1,947.0
cif-standard	0.068 (0.018)	0.745 (0.029)	8.817	11.4	4.397	24.3
cif-extension	0.066 (0.014)	0.746 (0.025)	45.390	58.6	6.577	36.4
aorsf-cph	0.065 (0.031)	0.745 (0.024)	1.280	1.65	0.179	0.992
aorsf-fast	0.063 (0.031)	0.744 (0.024)	0.774	1.00	0.181	1.00
ranger-extratrees	0.061 (0.024)	0.740 (0.028)	0.224	0.290	0.180	0.997
glmnet-cox	0.043 (0.034)	0.723 (0.037)	5.608	7.24	0.005	0.028
xgboost-cox	0.040 (0.014)	0.743 (0.026)	2.236	2.89	0.007	0.039
aorsf-random	0.030 (0.015)	0.699 (0.036)	1.847	2.38	0.190	1.05
rsf-standard	0.020 (0.041)	0.693 (0.033)	0.382	0.493	0.666	3.69
aorsf-net	0.003 (0.067)	0.740 (0.022)	464.082	599.3	0.179	0.992
nn-cox	-0.008 (0.065)	0.689 (0.045)	18.607	24.0	1.926	10.7
xgboost-aft	-3.09 (0.664)	0.742 (0.022)	11.258	14.5	0.010	0.056
FCL; death, n = 541, p = 7						
glmnet-cox	0.117 (0.028)	0.787 (0.037)	0.110	1.24	0.003	0.158
aorsf-cph	0.101 (0.039)	0.769 (0.034)	0.171	1.93	0.020	1.05
aorsf-fast	0.100 (0.038)	0.768 (0.033)	0.088	1.00	0.019	1.00
aorsf-net	0.097 (0.040)	0.760 (0.034)	13.429	151.8	0.020	1.06
obliqueRSF-net	0.089 (0.027)	0.758 (0.036)	108.537	1,226.6	5.743	302.0
cif-rotate	0.087 (0.048)	0.755 (0.027)	6.229	70.4	2.161	113.6
cif-extension	0.087 (0.036)	0.730 (0.034)	6.111	69.1	2.473	130.0
aorsf-random	0.087 (0.029)	0.757 (0.032)	0.304	3.44	0.020	1.05
cif-standard	0.084 (0.038)	0.743 (0.036)	0.793	8.97	1.275	67.1
ranger-extratrees	0.073 (0.016)	0.741 (0.037)	0.036	0.409	0.087	4.56
rsf-standard	0.072 (0.048)	0.732 (0.034)	0.526	5.94	0.039	2.07
xgboost-cox	0.029 (0.050)	0.679 (0.121)	0.342	3.87	0.002	0.105
nn-cox	-0.006 (0.015)	0.536 (0.097)	12.668	143.2	0.444	23.3
xgboost-aft	-2.52 (0.477)	0.754 (0.038)	7.286	82.3	0.006	0.316
FCL; relapse, n = 541, p = 7						
glmnet-cox	0.029 (0.017)	0.620 (0.024)	0.101	0.798	0.002	0.075
ranger-extratrees	0.017 (0.016)	0.596 (0.025)	0.034	0.270	0.091	3.36
obliqueRSF-net	0.013 (0.016)	0.592 (0.024)	245.138	1,943.8	11.109	411.1

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-random	0.012 (0.018)	0.595 (0.024)	0.473	3.75	0.024	0.892
xgboost-cox	0.010 (0.016)	0.598 (0.032)	1.315	10.4	0.003	0.111
cif-standard	0.007 (0.021)	0.594 (0.023)	0.950	7.54	1.722	63.7
aorsf-fast	0.007 (0.019)	0.594 (0.025)	0.126	1.00	0.027	1.00
aorsf-cph	0.007 (0.020)	0.594 (0.026)	0.272	2.16	0.028	1.04
aorsf-net	0.006 (0.020)	0.592 (0.026)	20.063	159.1	0.027	1.00
nn-cox	0.000 (0.019)	0.546 (0.054)	13.040	103.4	0.585	21.6
cif-extension	-0.005 (0.023)	0.580 (0.028)	6.550	51.9	3.603	133.3
cif-rotate	-0.012 (0.025)	0.583 (0.030)	7.129	56.5	3.081	114.0
rsf-standard	-0.027 (0.032)	0.577 (0.024)	1.048	8.31	0.087	3.22
xgboost-aft	-0.829 (0.337)	0.582 (0.034)	7.164	56.8	0.006	0.222
GBSG II; recurrence or death, n = 686, p = 10						
obliqueRSF-net	0.124 (0.016)	0.745 (0.017)	334.738	1,786.5	12.512	271.8
cif-standard	0.123 (0.020)	0.742 (0.019)	0.994	5.31	2.355	51.2
rsf-standard	0.120 (0.023)	0.737 (0.019)	1.669	8.91	0.113	2.46
aorsf-net	0.120 (0.024)	0.737 (0.020)	39.301	209.8	0.046	1.00
aorsf-cph	0.119 (0.025)	0.735 (0.019)	0.431	2.30	0.047	1.01
aorsf-fast	0.116 (0.024)	0.732 (0.017)	0.187	1.00	0.046	1.00
cif-extension	0.114 (0.017)	0.742 (0.019)	8.843	47.2	4.667	101.4
cif-rotate	0.107 (0.022)	0.729 (0.017)	12.995	69.4	5.199	112.9
aorsf-random	0.104 (0.024)	0.723 (0.025)	1.334	7.12	0.044	0.964
ranger-extratrees	0.094 (0.018)	0.736 (0.025)	0.099	0.526	0.132	2.87
glmnet-cox	0.091 (0.019)	0.727 (0.021)	0.141	0.752	0.003	0.065
xgboost-cox	0.083 (0.017)	0.729 (0.020)	2.577	13.8	0.003	0.065
nn-cox	-0.004 (0.004)	0.524 (0.065)	12.618	67.3	1.165	25.3
xgboost-aft	-1.10 (0.162)	0.729 (0.021)	11.930	63.7	0.007	0.152
GUIDE-IT; CVD death, n = 894, p = 59						
aorsf-fast	0.075 (0.018)	0.746 (0.027)	0.174	1.00	0.037	1.00
aorsf-net	0.074 (0.019)	0.743 (0.027)	28.658	164.8	0.040	1.09
aorsf-cph	0.072 (0.018)	0.743 (0.026)	0.405	2.33	0.040	1.08
glmnet-cox	0.063 (0.041)	0.715 (0.091)	0.921	5.30	0.003	0.081
obliqueRSF-net	0.063 (0.013)	0.741 (0.023)	251.024	1,443.1	11.754	317.4
cif-rotate	0.059 (0.016)	0.721 (0.025)	37.291	214.4	4.884	131.9
cif-standard	0.058 (0.014)	0.737 (0.022)	2.228	12.8	3.646	98.5
ranger-extratrees	0.054 (0.013)	0.737 (0.029)	0.715	4.11	0.206	5.57
cif-extension	0.052 (0.011)	0.730 (0.022)	13.957	80.2	5.770	155.8
rsf-standard	0.046 (0.023)	0.705 (0.025)	1.219	7.01	0.075	2.03

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
xgboost-cox	0.039 (0.051)	0.747 (0.020)	4.233	24.3	0.003	0.081
aorsf-random	0.033 (0.012)	0.695 (0.030)	1.324	7.61	0.041	1.11
nn-cox	0.024 (0.036)	0.686 (0.082)	12.885	74.1	0.602	16.3
xgboost-aft	-5.15 (0.987)	0.734 (0.020)	13.101	75.3	0.007	0.189
GUIDE-IT; HF hospitalization, n = 894, p = 59						
aorsf-net	0.082 (0.017)	0.722 (0.023)	59.048	213.7	0.069	1.13
aorsf-cph	0.082 (0.018)	0.722 (0.023)	0.711	2.57	0.063	1.02
aorsf-fast	0.082 (0.019)	0.722 (0.025)	0.276	1.00	0.062	1.00
ranger-extratrees	0.074 (0.010)	0.723 (0.022)	0.703	2.54	0.215	3.49
obliqueRSF-net	0.074 (0.010)	0.721 (0.023)	468.654	1,695.9	14.749	239.1
cif-standard	0.071 (0.010)	0.716 (0.023)	1.958	7.09	3.737	60.6
cif-rotate	0.068 (0.018)	0.708 (0.029)	45.430	164.4	6.497	105.3
cif-extension	0.064 (0.009)	0.714 (0.022)	17.887	64.7	8.557	138.7
rsf-standard	0.059 (0.022)	0.694 (0.026)	1.390	5.03	0.112	1.81
glmnet-cox	0.058 (0.019)	0.699 (0.024)	0.980	3.54	0.003	0.049
aorsf-random	0.050 (0.010)	0.682 (0.023)	1.716	6.21	0.062	1.01
xgboost-cox	0.039 (0.017)	0.698 (0.027)	3.225	11.7	0.003	0.049
nn-cox	0.038 (0.028)	0.683 (0.068)	13.970	50.6	0.640	10.4
xgboost-aft	-2.16 (0.322)	0.696 (0.026)	12.919	46.8	0.006	0.097
Heart Transplant; graft-loss or death, n = 3787, p = 52						
cif-rotate	0.056 (0.010)	0.731 (0.017)	161.908	167.2	34.174	110.4
aorsf-net	0.053 (0.006)	0.733 (0.013)	132.397	136.8	0.313	1.01
aorsf-fast	0.052 (0.006)	0.735 (0.014)	0.968	1.00	0.309	1.00
aorsf-cph	0.051 (0.006)	0.733 (0.013)	3.094	3.20	0.312	1.01
cif-standard	0.050 (0.006)	0.733 (0.013)	11.540	11.9	43.325	140.0
obliqueRSF-net	0.049 (0.006)	0.730 (0.014)	363.594	375.6	168.051	543.1
rsf-standard	0.048 (0.009)	0.727 (0.013)	3.516	3.63	1.110	3.59
ranger-extratrees	0.046 (0.006)	0.730 (0.013)	5.812	6.00	3.555	11.5
glmnet-cox	0.036 (0.006)	0.711 (0.016)	1.023	1.06	0.012	0.039
cif-extension	0.036 (0.004)	0.726 (0.016)	51.192	52.9	25.128	81.2
xgboost-cox	0.031 (0.007)	0.716 (0.018)	3.516	3.63	0.011	0.036
aorsf-random	0.029 (0.003)	0.693 (0.014)	3.220	3.33	0.292	0.944
nn-cox	0.023 (0.012)	0.677 (0.036)	17.152	17.7	11.675	37.7
xgboost-aft	-4.30 (0.486)	0.724 (0.013)	13.829	14.3	0.009	0.029
Monoclonal gammopathy; death, n = 1384, p = 8						
cif-rotate	0.160 (0.019)	0.744 (0.014)	16.541	35.9	7.904	71.1
aorsf-cph	0.159 (0.016)	0.742 (0.011)	1.239	2.69	0.111	0.995

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-fast	0.158 (0.016)	0.742 (0.011)	0.461	1.00	0.111	1.00
aorsf-net	0.156 (0.016)	0.741 (0.011)	99.187	215.0	0.109	0.977
obliqueRSF-net	0.156 (0.013)	0.743 (0.011)	239.204	518.6	17.341	155.9
cif-standard	0.151 (0.015)	0.738 (0.012)	2.162	4.69	8.068	72.6
rsf-standard	0.151 (0.017)	0.737 (0.011)	2.044	4.43	0.191	1.72
aorsf-random	0.146 (0.014)	0.735 (0.012)	2.586	5.61	0.104	0.940
cif-extension	0.144 (0.010)	0.747 (0.013)	11.336	24.6	6.951	62.5
glmnet-cox	0.138 (0.021)	0.727 (0.014)	0.140	0.304	0.004	0.036
xgboost-cox	0.123 (0.012)	0.733 (0.012)	3.706	8.03	0.005	0.045
ranger-extratrees	0.116 (0.005)	0.744 (0.012)	0.083	0.179	0.193	1.74
nn-cox	0.032 (0.057)	0.614 (0.096)	15.851	34.4	1.119	10.1
xgboost-aft	-0.840 (0.148)	0.733 (0.013)	13.195	28.6	0.010	0.087
Monoclonal gammopathy; malignancy, n = 1384, p = 8						
glmnet-cox	0.015 (0.011)	0.651 (0.055)	0.119	0.587	0.002	0.048
aorsf-cph	0.010 (0.013)	0.643 (0.036)	0.608	3.01	0.043	1.02
aorsf-fast	0.010 (0.014)	0.641 (0.036)	0.202	1.00	0.042	1.00
ranger-extratrees	0.008 (0.006)	0.642 (0.030)	0.072	0.356	0.785	18.6
cif-extension	0.008 (0.010)	0.625 (0.028)	9.606	47.5	5.217	123.3
obliqueRSF-net	0.007 (0.010)	0.628 (0.033)	44.947	222.2	16.670	393.9
aorsf-net	0.007 (0.014)	0.641 (0.034)	25.311	125.1	0.043	1.02
aorsf-random	0.007 (0.013)	0.633 (0.033)	1.367	6.76	0.042	0.993
xgboost-cox	0.007 (0.017)	0.639 (0.039)	1.886	9.32	0.003	0.071
cif-standard	0.006 (0.011)	0.628 (0.033)	1.730	8.55	5.759	136.1
nn-cox	-0.003 (0.005)	0.505 (0.041)	12.035	59.5	1.253	29.6
rsf-standard	-0.009 (0.018)	0.616 (0.036)	0.906	4.48	0.075	1.77
cif-rotate	-0.024 (0.023)	0.553 (0.035)	13.627	67.4	4.933	116.6
xgboost-aft	-5.59 (0.998)	0.629 (0.039)	10.872	53.7	0.007	0.166
Movies released in 2015-2018; gross 1M USD, n = 551, p = 46						
cif-rotate	0.639 (0.023)	0.943 (0.007)	21.710	79.3	6.039	105.1
glmnet-cox	0.620 (0.033)	0.940 (0.009)	0.200	0.730	0.003	0.052
nn-cox	0.542 (0.082)	0.906 (0.032)	19.966	72.9	0.768	13.4
aorsf-net	0.531 (0.027)	0.928 (0.010)	55.942	204.3	0.060	1.05
aorsf-cph	0.523 (0.024)	0.925 (0.011)	0.810	2.96	0.059	1.03
rsf-standard	0.520 (0.021)	0.922 (0.010)	1.472	5.37	0.103	1.79
aorsf-fast	0.517 (0.026)	0.922 (0.012)	0.274	1.00	0.057	1.00
xgboost-cox	0.511 (0.028)	0.932 (0.009)	13.948	50.9	0.006	0.104
cif-standard	0.475 (0.028)	0.902 (0.018)	0.817	2.98	2.096	36.5

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
cif-extension	0.455 (0.024)	0.920 (0.013)	9.786	35.7	6.061	105.4
ranger-extratrees	0.431 (0.025)	0.900 (0.019)	0.079	0.289	0.114	1.98
obliqueRSF-net	0.320 (0.022)	0.909 (0.017)	155.578	568.2	27.372	476.1
aorsf-random	0.300 (0.031)	0.849 (0.027)	1.481	5.41	0.053	0.923
xgboost-aft	-0.477 (0.082)	0.927 (0.010)	48.721	177.9	0.009	0.156
Non-alcohol fatty liver disease; death, n = 17549, p = 24						
aorsf-cph	0.215 (0.008)	0.868 (0.005)	19.970	3.60	15.802	1.40
aorsf-fast	0.215 (0.009)	0.869 (0.005)	5.540	1.00	11.287	1.00
aorsf-net	0.213 (0.008)	0.864 (0.006)	502.140	90.6	10.259	0.909
obliqueRSF-net	0.212 (0.008)	0.868 (0.006)	1536.877	277.4	6754.575	598.4
rsf-standard	0.210 (0.009)	0.860 (0.005)	12.179	2.20	1.378	0.122
glmnet-cox	0.209 (0.011)	0.861 (0.005)	1.900	0.343	0.876	0.078
cif-standard	0.208 (0.007)	0.863 (0.006)	72.584	13.1	753.937	66.8
cif-rotate	0.193 (0.008)	0.866 (0.005)	288.250	52.0	224.923	19.9
ranger-extratrees	0.183 (0.007)	0.860 (0.005)	46.126	8.33	146.397	13.0
cif-extension	0.168 (0.003)	0.866 (0.006)	129.626	23.4	211.122	18.7
aorsf-random	0.142 (0.007)	0.838 (0.007)	15.152	2.73	14.820	1.31
xgboost-cox	0.023 (0.015)	0.876 (0.005)	8.989	1.62	1.026	0.091
nn-cox	-0.001 (0.009)	0.577 (0.108)	31.442	5.68	192.811	17.1
xgboost-aft	-7.27 (0.765)	0.875 (0.005)	28.699	5.18	0.807	0.072
Primary biliary cholangitis; death, n = 276, p = 19						
aorsf-fast	0.430 (0.033)	0.908 (0.021)	0.081	1.00	0.020	1.00
aorsf-cph	0.418 (0.034)	0.906 (0.021)	0.161	2.00	0.020	0.996
aorsf-net	0.412 (0.035)	0.905 (0.022)	16.130	200.3	0.020	1.00
cif-rotate	0.405 (0.041)	0.899 (0.022)	9.930	123.3	2.165	107.7
rsf-standard	0.391 (0.034)	0.895 (0.023)	0.111	1.37	0.040	2.01
obliqueRSF-net	0.369 (0.032)	0.906 (0.022)	114.388	1,420.7	1.934	96.2
aorsf-random	0.354 (0.031)	0.893 (0.020)	0.373	4.63	0.020	1.00
cif-standard	0.351 (0.034)	0.904 (0.025)	0.241	2.99	1.152	57.3
cif-extension	0.348 (0.033)	0.901 (0.023)	9.607	119.3	3.745	186.4
glmnet-cox	0.342 (0.045)	0.886 (0.028)	0.115	1.43	0.002	0.101
ranger-extratrees	0.276 (0.028)	0.894 (0.027)	0.028	0.348	0.040	2.00
xgboost-cox	0.256 (0.104)	0.881 (0.027)	4.597	57.1	0.003	0.149
nn-cox	-0.035 (0.064)	0.577 (0.166)	11.413	141.7	0.242	12.0
xgboost-aft	-0.953 (0.305)	0.883 (0.024)	8.994	111.7	0.006	0.299
Rotterdam tumor bank; death, n = 2982, p = 11						
aorsf-net	0.167 (0.012)	0.762 (0.009)	158.184	167.0	0.393	0.928

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
obliqueRSF-net	0.164 (0.010)	0.761 (0.009)	522.346	551.5	122.804	289.7
aorsf-cph	0.164 (0.012)	0.758 (0.009)	2.691	2.84	0.421	0.994
aorsf-fast	0.162 (0.012)	0.757 (0.009)	0.947	1.00	0.424	1.00
cif-standard	0.160 (0.010)	0.759 (0.009)	7.041	7.43	43.238	102.0
rsf-standard	0.160 (0.014)	0.756 (0.009)	2.859	3.02	0.865	2.04
aorsf-random	0.154 (0.010)	0.752 (0.010)	4.162	4.39	0.392	0.925
cif-rotate	0.148 (0.011)	0.750 (0.011)	34.744	36.7	29.541	69.7
ranger-extratrees	0.140 (0.006)	0.748 (0.009)	3.506	3.70	2.848	6.72
xgboost-cox	0.131 (0.014)	0.753 (0.010)	4.796	5.06	0.020	0.047
cif-extension	0.131 (0.004)	0.751 (0.008)	23.585	24.9	30.945	73.0
glmnet-cox	0.119 (0.008)	0.731 (0.009)	0.671	0.708	0.018	0.043
nn-cox	-0.005 (0.011)	0.506 (0.043)	17.750	18.7	9.921	23.4
xgboost-aft	-1.34 (0.161)	0.761 (0.009)	14.771	15.6	0.010	0.024
Rotterdam tumor bank; recurrence, n = 2982, p = 11						
obliqueRSF-net	0.148 (0.010)	0.737 (0.009)	547.423	508.8	133.525	289.3
aorsf-net	0.147 (0.011)	0.735 (0.009)	168.357	156.5	0.425	0.922
aorsf-cph	0.145 (0.011)	0.734 (0.009)	2.986	2.78	0.453	0.981
cif-standard	0.145 (0.011)	0.734 (0.009)	5.054	4.70	30.784	66.7
aorsf-fast	0.143 (0.011)	0.733 (0.009)	1.076	1.00	0.462	1.00
aorsf-random	0.140 (0.010)	0.730 (0.008)	4.277	3.97	0.423	0.917
rsf-standard	0.139 (0.012)	0.731 (0.008)	3.016	2.80	0.372	0.806
ranger-extratrees	0.135 (0.007)	0.733 (0.009)	3.616	3.36	2.835	6.14
cif-rotate	0.130 (0.010)	0.725 (0.009)	37.506	34.9	35.411	76.7
cif-extension	0.119 (0.006)	0.731 (0.008)	24.957	23.2	29.569	64.1
glmnet-cox	0.118 (0.008)	0.727 (0.008)	0.706	0.656	0.028	0.061
xgboost-cox	0.114 (0.008)	0.729 (0.009)	3.816	3.55	0.020	0.044
nn-cox	-0.002 (0.002)	0.534 (0.068)	21.275	19.8	9.967	21.6
xgboost-aft	-1.01 (0.129)	0.735 (0.009)	15.443	14.4	0.010	0.022
Serum free light chain; death, n = 7874, p = 10						
aorsf-fast	0.252 (0.014)	0.825 (0.007)	2.664	1.00	4.471	1.00
aorsf-cph	0.252 (0.013)	0.825 (0.008)	7.125	2.67	5.990	1.34
aorsf-net	0.252 (0.012)	0.823 (0.008)	320.194	120.2	5.152	1.15
glmnet-cox	0.249 (0.012)	0.820 (0.007)	1.217	0.457	0.099	0.022
obliqueRSF-net	0.249 (0.011)	0.821 (0.008)	1170.382	439.3	814.990	182.3
ranger-extratrees	0.245 (0.009)	0.820 (0.007)	15.036	5.64	13.481	3.02
cif-standard	0.245 (0.011)	0.818 (0.008)	20.391	7.65	155.387	34.8
rsf-standard	0.245 (0.013)	0.815 (0.008)	5.872	2.20	0.575	0.129

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-random	0.233 (0.012)	0.816 (0.008)	9.238	3.47	4.902	1.10
cif-rotate	0.230 (0.009)	0.819 (0.007)	67.494	25.3	137.166	30.7
cif-extension	0.203 (0.005)	0.820 (0.008)	44.122	16.6	162.158	36.3
xgboost-cox	0.097 (0.038)	0.824 (0.007)	6.133	2.30	0.101	0.023
nn-cox	0.003 (0.006)	0.612 (0.135)	25.297	9.49	27.315	6.11
xgboost-aft	-2.71 (0.293)	0.823 (0.008)	22.227	8.34	0.035	0.008
sim						
aorsf-net	0.034 (0.022)	0.632 (0.038)	224.558	187.4	72.991	1.36
aorsf-cph	0.033 (0.023)	0.635 (0.038)	3.021	2.52	61.620	1.15
aorsf-fast	0.029 (0.023)	0.636 (0.038)	1.198	1.00	53.771	1.00
aorsf-random	0.029 (0.013)	0.616 (0.033)	7.759	6.47	68.892	1.28
obliqueRSF-net	0.027 (0.016)	0.613 (0.043)	910.443	759.7	380.178	7.07
cif-standard	0.023 (0.015)	0.603 (0.043)	6.188	5.16	231.294	4.30
cif-rotate	0.020 (0.021)	0.592 (0.051)	316.904	264.4	801.648	14.9
rsf-standard	0.019 (0.014)	0.610 (0.032)	5.788	4.83	2.322	0.043
ranger-extratrees	0.018 (0.008)	0.620 (0.037)	4.820	4.02	6.453	0.120
cif-extension	0.015 (0.008)	0.599 (0.040)	107.025	89.3	1030.394	19.2
xgboost-cox	-0.023 (0.043)	0.616 (0.039)	17.126	14.3	1.747	0.032
glmnet-cox	-0.036 (0.064)	0.616 (0.040)	0.545	0.455	1.462	0.027
nn-cox	-0.059 (0.071)	0.616 (0.043)	29.897	24.9	18.594	0.346
xgboost-aft	-1.66 (0.126)	0.624 (0.038)	52.084	43.5	1.380	0.026
SPRINT; CVD death, n = 9361, p = 174						
glmnet-cox	0.072 (0.011)	0.796 (0.011)	14.356	4.42	0.033	0.036
aorsf-net	0.071 (0.007)	0.796 (0.011)	343.232	105.7	0.949	1.05
aorsf-cph	0.070 (0.006)	0.798 (0.011)	9.991	3.08	0.971	1.07
aorsf-fast	0.070 (0.006)	0.798 (0.011)	3.248	1.00	0.908	1.00
obliqueRSF-net	0.068 (0.004)	0.798 (0.012)	1161.784	357.7	1311.066	1,444.0
rsf-standard	0.065 (0.007)	0.789 (0.014)	5.167	1.59	0.685	0.755
cif-standard	0.062 (0.003)	0.798 (0.011)	51.058	15.7	199.723	220.0
cif-rotate	0.061 (0.005)	0.791 (0.012)	1033.390	318.1	136.883	150.8
ranger-extratrees	0.055 (0.003)	0.792 (0.012)	8.015	2.47	9.226	10.2
nn-cox	0.040 (0.013)	0.765 (0.017)	24.177	7.44	33.019	36.4
cif-extension	0.034 (0.002)	0.790 (0.011)	123.690	38.1	53.842	59.3
aorsf-random	0.027 (0.002)	0.747 (0.016)	6.889	2.12	1.101	1.21
xgboost-cox	0.006 (0.017)	0.800 (0.011)	7.910	2.44	0.033	0.036
xgboost-aft	-10.8 (1.01)	0.796 (0.012)	24.603	7.57	0.016	0.018
SPRINT; death, n = 9361, p = 174						

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
glmnet-cox	0.124 (0.012)	0.771 (0.009)	5.349	1.10	0.080	0.016
aorsf-cph	0.118 (0.008)	0.770 (0.008)	14.219	2.92	3.629	0.751
aorsf-fast	0.117 (0.008)	0.770 (0.008)	4.874	1.00	4.833	1.00
aorsf-net	0.114 (0.009)	0.769 (0.009)	657.473	134.9	4.336	0.897
obliqueRSF-net	0.113 (0.007)	0.767 (0.008)	3057.859	627.3	1289.532	266.8
rsf-standard	0.111 (0.008)	0.763 (0.009)	6.755	1.39	0.729	0.151
cif-standard	0.107 (0.006)	0.764 (0.008)	46.959	9.63	212.057	43.9
nn-cox	0.099 (0.014)	0.757 (0.011)	68.533	14.1	64.373	13.3
ranger-extratrees	0.097 (0.005)	0.756 (0.009)	11.099	2.28	11.653	2.41
cif-rotate	0.092 (0.007)	0.745 (0.009)	1108.036	227.3	188.939	39.1
cif-extension	0.056 (0.002)	0.747 (0.009)	139.289	28.6	103.221	21.4
aorsf-random	0.053 (0.003)	0.720 (0.010)	13.605	2.79	4.437	0.918
xgboost-cox	0.031 (0.023)	0.772 (0.008)	9.951	2.04	0.084	0.017
xgboost-aft	-4.41 (0.302)	0.772 (0.008)	28.705	5.89	0.653	0.135
Systolic Heart Failure; death, n = 2231, p = 41						
obliqueRSF-net	0.114 (0.012)	0.747 (0.012)	407.606	340.6	60.875	257.1
glmnet-cox	0.114 (0.013)	0.746 (0.012)	0.791	0.661	0.019	0.080
cif-rotate	0.113 (0.013)	0.741 (0.011)	72.623	60.7	22.449	94.8
aorsf-net	0.112 (0.013)	0.743 (0.012)	125.118	104.6	0.243	1.03
aorsf-cph	0.111 (0.014)	0.744 (0.012)	2.822	2.36	0.237	1.00
aorsf-fast	0.110 (0.015)	0.744 (0.011)	1.197	1.00	0.237	1.00
cif-standard	0.110 (0.011)	0.744 (0.011)	5.168	4.32	22.720	96.0
rsf-standard	0.105 (0.011)	0.735 (0.011)	2.800	2.34	0.304	1.29
cif-extension	0.094 (0.006)	0.744 (0.012)	30.964	25.9	19.184	81.0
ranger-extratrees	0.092 (0.008)	0.738 (0.012)	4.404	3.68	1.442	6.09
xgboost-cox	0.090 (0.009)	0.744 (0.010)	4.784	4.00	0.010	0.042
aorsf-random	0.080 (0.006)	0.731 (0.013)	3.206	2.68	0.230	0.974
nn-cox	0.077 (0.024)	0.711 (0.023)	23.045	19.3	5.516	23.3
xgboost-aft	-1.98 (0.218)	0.742 (0.009)	14.099	11.8	0.010	0.042
VA lung cancer trial; death, n = 137, p = 8						
aorsf-net	0.201 (0.051)	0.797 (0.035)	10.595	189.0	0.013	1.07
aorsf-fast	0.200 (0.050)	0.795 (0.034)	0.056	1.00	0.012	1.00
cif-rotate	0.198 (0.066)	0.788 (0.036)	4.899	87.4	1.095	90.3
aorsf-cph	0.198 (0.052)	0.794 (0.035)	0.104	1.85	0.012	0.998
rsf-standard	0.175 (0.048)	0.787 (0.037)	0.083	1.48	0.030	2.46
cif-extension	0.173 (0.048)	0.795 (0.034)	5.230	93.3	1.640	135.3
glmnet-cox	0.160 (0.036)	0.787 (0.038)	0.091	1.62	0.002	0.165

(continued)

	Scaled Brier	C-Statistic	Median	Ratio	Median	Ratio
aorsf-random	0.154 (0.045)	0.780 (0.037)	0.226	4.04	0.012	0.991
cif-standard	0.128 (0.040)	0.770 (0.037)	0.096	1.71	0.122	10.1
obliqueRSF-net	0.126 (0.034)	0.796 (0.029)	65.750	1,173.0	0.688	56.8
ranger-extratrees	0.091 (0.033)	0.778 (0.038)	0.021	0.377	0.029	2.42
xgboost-cox	0.068 (0.078)	0.750 (0.046)	1.291	23.0	0.002	0.165
xgboost-aft	-0.009 (0.136)	0.753 (0.047)	6.788	121.1	0.006	0.495
nn-cox	-0.039 (0.036)	0.505 (0.078)	11.297	201.6	0.165	13.6

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